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Score-based Likelihood Ratios for Camera Device Identification

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The camera device identification problem

- A type of **specific source identification problem**
- Scenario:
  - Evidence
    - *Unknown source evidence* - Digital image e_u from an unknown camera device (source) is recovered as evidence in a crime
    - *Specific known source evidence* - A camera fingerprint e_s is estimated from a suspect's camera device (source) C_s
  - The prosecution wants to determine whether image e_u and camera fingerprint e_s originate from the same specific camera device C_s (the suspect's camera device)
  - <u>Assumption:</u> the prosecution has access to the suspect's camera C_s and is able to take images on it to be used in analysis

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The camera device identification problem

- The prosecution and defense hypotheses:
  - H_p: image e_u and camera fingerprint e_s originate from the same specific camera device C_s
  - H_d: image e_u and camera fingerprint e_s do not originate from the same specific camera device C_s
- The end goal is to determine whether the evidence supports H_p or H_d
- Terminology
  - *Match* – an image and a camera fingerprint originate from the same camera device
  - *Non-match* – an image and a camera fingerprint no not originate from the same camera device

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Score-based likelihood ratios (SLR)

- Quantify the weight of forensic evidence
  - Describe the strength of evidence in favor of *match* or *non-match*, giving stakeholders more information than a binary decision of *match* or *non-match*
- Implemented in handwriting[1], shoeprint[2], and glass evidence[2]
- Limited implementation in camera device identifcation[3,4]

1. Hepler, Amanda B., Christopher P. Saunders, Linda J. Davis, and JoAnn Buscaglia. "Score-based likelihood ratios for handwriting evidence." Forensic science international 219, no. 1-3 (2012): 129-140.
2. Park, Soyoung. "Learning algorithms for forensic science applications." (2018).
3. Nordgaard, Anders, and Tobias Höglund. "Assessment of approximate likelihood ratios from continuous distributions: a case study of digital camera identification." *Journal of forensic sciences* 56, no. 2 (2011): 390-402.
4. van Houten, Wiger, Ivo Alberink, and Zeno Geradts. "Implementation of the likelihood ratio framework for camera identification based on sensor noise patterns." *Law, Probability and Risk* 10, no. 2 (2011): 149-159.

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Score-based likelihood ratios v. Likelihood Ratios

Score-based likelihood ratios

- Model similarity scores applied to features

Likelihood ratios

- Directly model features

SLRs and LRs have different statistical properties![1]

1. Neumann, Cedric, and Madeline A. Ausdemore. "Defence Against the Modern Arts: the Curse of Statistics 'Score-based likelihood ratios'." arXiv preprint arXiv:1910.05240 (2019).

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Score-based likelihood ratios (SLR)

- The SLR measures the relative probability of obtaining the similarity score $\delta = \Delta(e_u, e_s)$ if the image e_u and camera fingerprint e_s originate from the same specific camera device

$$SLR = \frac{P(\Delta(e_u, e_s) = \delta \mid e_s,\ H_p)}{P(\Delta(e_u, e_s) = \delta \mid e_u,\ H_d\ )}$$

there are 3 ways to define this[1]

1. Hepler, Amanda B., Christopher P. Saunders, Linda J. Davis, and JoAnn Buscaglia. "Score-based likelihood ratios for handwriting evidence." Forensic science international 219, no. 1-3 (2012): 129-140.

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Three methods for defining and calculating non-matches

1. Source-anchored (fix specific device C_s)[1]
   - Calculate scores between camera fingerprints from C_s and images from other devices
2. Trace-anchored (fix specific image e_u)[1]
   - Calculate scores between the image e_u and camera fingerprints of devices other than specific device C_s
3. General match (don't fix C_s or e_u)[1]
   - Calculate scores between an image from a randomly selected camera other than C_s and the camera fingerprint of a second camera other than C_s

- Each method may result in a different distribution[1]

1. Hepler, Amanda B., Christopher P. Saunders, Linda J. Davis, and JoAnn Buscaglia. "Score-based likelihood ratios for handwriting evidence." Forensic science international 219, no. 1-3 (2012): 129-140.

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Definitions of non-matches used in prior device id work

Source-anchored

Lukas, Fridrich, and Goljan 2005

Chen, Fridrich, and Goljan 2007

Chen et. al. 2008

Hu, Yu, and Jian 2009

Nordgaard and Hoglund 2011

van Houten et. al. 2011

Costa et. al. 2012

Goljan and Fridrich 2012

Trace-anchored

Lukas, Fridrich, and Goljan 2005

General Match

Goljan, Fridrich, and Filler 2009

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Definitions of non-matches used in prior device id work

Source-anchored

Lukas, Fridrich, and Goljan 2005

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Chen et. al. 2008

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Nordgaard and Hoglund 2011

van Houten et. al. 2011

Costa et. al. 2012

Goljan and Fridrich 2012

Trace-anchored

Lukas, Fridrich, and Goljan 2005

We use this method

General Match

Goljan, Fridrich, and Filler 2009

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Prior work with SLRs in device identification

- Nordgaard and Höglund[1]
  - Introduced SLRs for camera device identification
  - Only considered two devices
  - Only implemented the source-anchored definition of non-matches
- van Houten, Alberink and Geradts[2]
  - Expanded Nordgaard and Höglund's results to more devices
  - Only implemented the source-anchored definition of non-matches
- Our research
  - Current work - Implement trace-anchored SLRs in device id for the first time
  - Future work – compare results of all three methods in SLRs

1. Nordgaard, Anders, and Tobias Höglund. "Assessment of approximate likelihood ratios from continuous distributions: a case study of digital camera identification." *Journal of forensic sciences* 56, no. 2 (2011): 390-402.
2. van Houten, Wiger, Ivo Alberink, and Zeno Geradts. "Implementation of the likelihood ratio framework for camera identification based on sensor noise patterns." *Law, Probability and Risk* 10, no. 2 (2011): 149-159.

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Comparing SLR approach and previous approach to camera device identification

Universal Detector

- Most widely used approach to camera device identification
- The goal is to develop a statistically sound, relevant set of scores that can be applied to any image and device
- If e_u or e_s changes, a new set of scores <u>does not</u> need to be generated
- Outcome: Binary decision

Score-based likelihood ratios

- The goal is to create statistically sound, relevant sets of *matching* and *non-matching* scores specific to image e_u and camera fingerprint e_s
- If e_u or e_s changes, a new relevant set of scores is generated
- Outcome: Quantification of the weight of evidence – A real number greater than or equal to zero

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Photo Response Non-Uniformity (PRNU)

- Used as a *camera fingerprint*[1]
- Result of sensor imperfections
- Estimated from flat-field or natural images with a denoising filter[1, 2]
- In the camera device identification problem
  - Estimate the noise residual of questioned image e_u
  - Estimate the PRNU or camera fingerprint e_s of specific known device C_s

1. Lukas, Jan, Jessica Fridrich, and Miroslav Goljan. "Determining digital image origin using sensor imperfections." In Image and Video Communications and Processing 2005, vol. 5685, pp. 249-260. International Society for Optics and Photonics, 2005.
2. Goljan, Miroslav, Jessica Fridrich, and Tomáš Filler. "Large scale test of sensor fingerprint camera identification." In *Media forensics and security*, vol. 7254, p. 72540I. International Society for Optics and Photonics, 2009.

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Similarity scores

- In the universal detector approach
  - Normalized correlation used in earlier works[1]
  - Peak-to-Correlation Energy (PCE) replaced normalized correlation[2]
    - If using PCE, the decision threshold does not need to be adjusted if a periodic component such as linear pattern is present
    - If using PCE, the decision threshold does not need to be recalculated if the image size changes

1. Lukas, Jan, Jessica Fridrich, and Miroslav Goljan. "Determining digital image origin using sensor imperfections." In Image and Video Communications and Processing 2005, vol. 5685, pp. 249-260. International Society for Optics and Photonics, 2005.
2. Goljan, Miroslav. "Digital camera identification from images–estimating false acceptance probability." In *International workshop on digital watermarking*, pp. 454-468. Springer, Berlin, Heidelberg, 2008.

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Similarity scores

- In the SLR approach
  - We use the score $\Delta(x,y) = 1 - \frac{(x-\bar{x})(y-\bar{y})}{\|x-\bar{x}\|\|y-\bar{y}\|}$ (One minus the normalized correlation)
  - Reason: Normalized correlation has much smaller variance than Peak to Correlation Energy (PCE), so it produces fewer 'inconclusive' instances where the SLR denominator is zero and the SLR numerator is tiny than PCE (more about this later)
  - Justification: Because the SLR approach does not use a decision threshold, the problems normalized correlation encounters in the universal detector approach are not problems for SLR

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Example using idealized data

Generate two sets of scores

Matching scores

- Scores between the noise residual of an image and the camera fingerprint of its source device

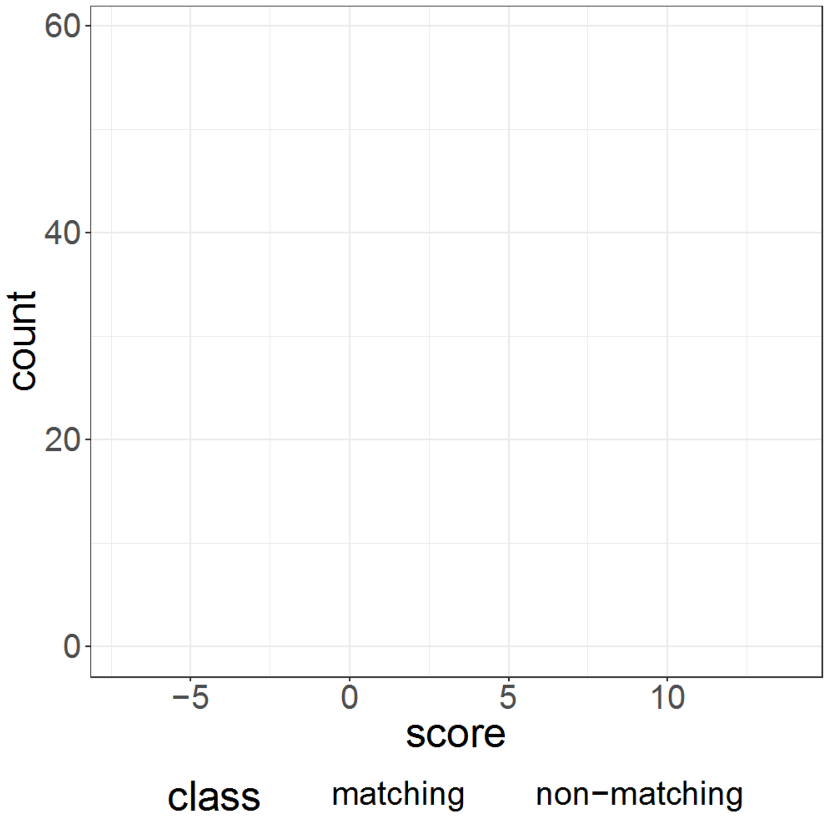
Non-matching scores

- Scores between the noise residual of an image and the camera fingerprint of another device

Example data

- Suppose matching scores follow a normal distribution $N(8,5)$ and non-matching scores follow a normal distribution $N(0,5)$

Histograms of 300 randomly generated matching and non-matching scores



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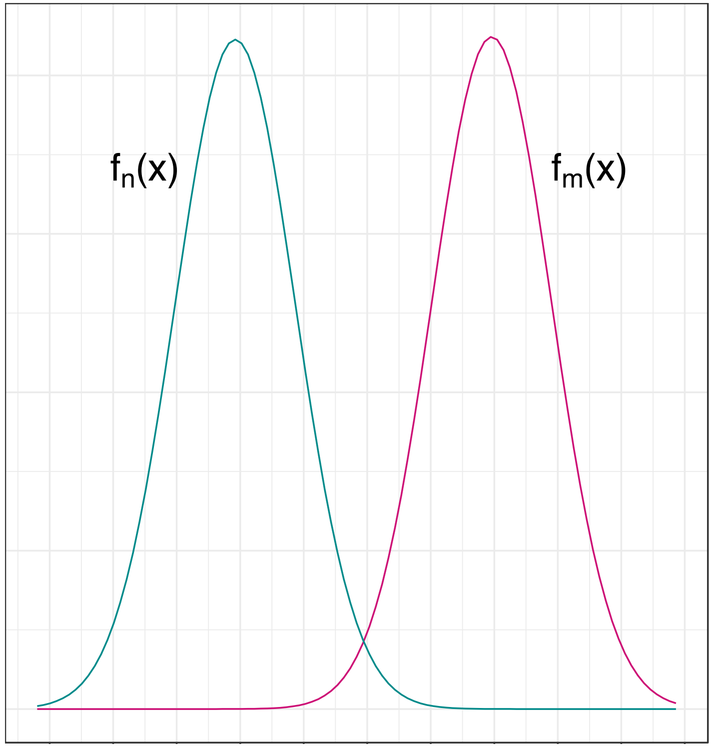
Fit pdfs to both sets of scores

Example

- Fit a normal probability density function to each set of scores

Normal pdfs fit to the matching and non-matching scores



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[Universal Detector]()

Set Threshold

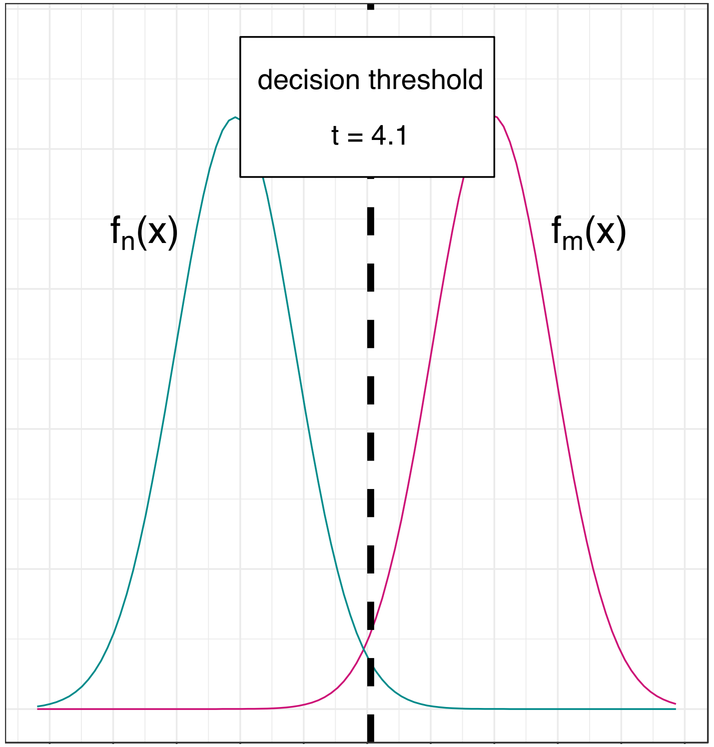
Choose decision threshold t

Typically chosen to produce a specific false acceptance rate

Example

- $t = 4.1$ yields a false acceptance rate of 0.01

The decision threshold and normal pdfs fit to the matching and non-matching scores



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Universal Detector

Set Threshold

Choose decision threshold t

Typically chosen to produce a specific false acceptance rate

Example

- $t = 4.1$ yields a false acceptance rate of 0.01

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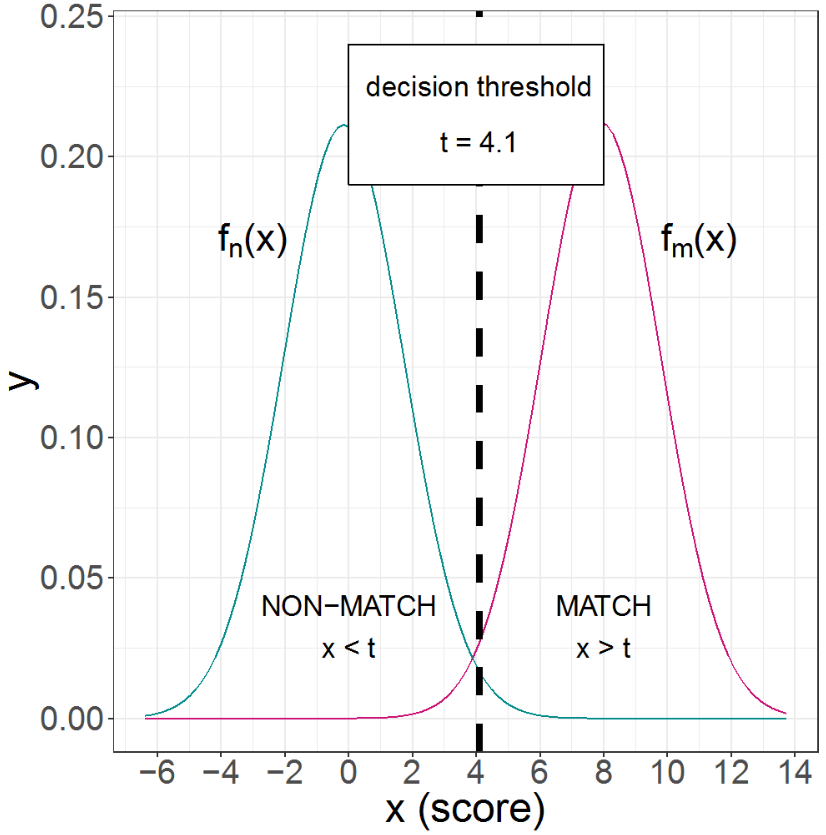

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Universal Detector

Make decision

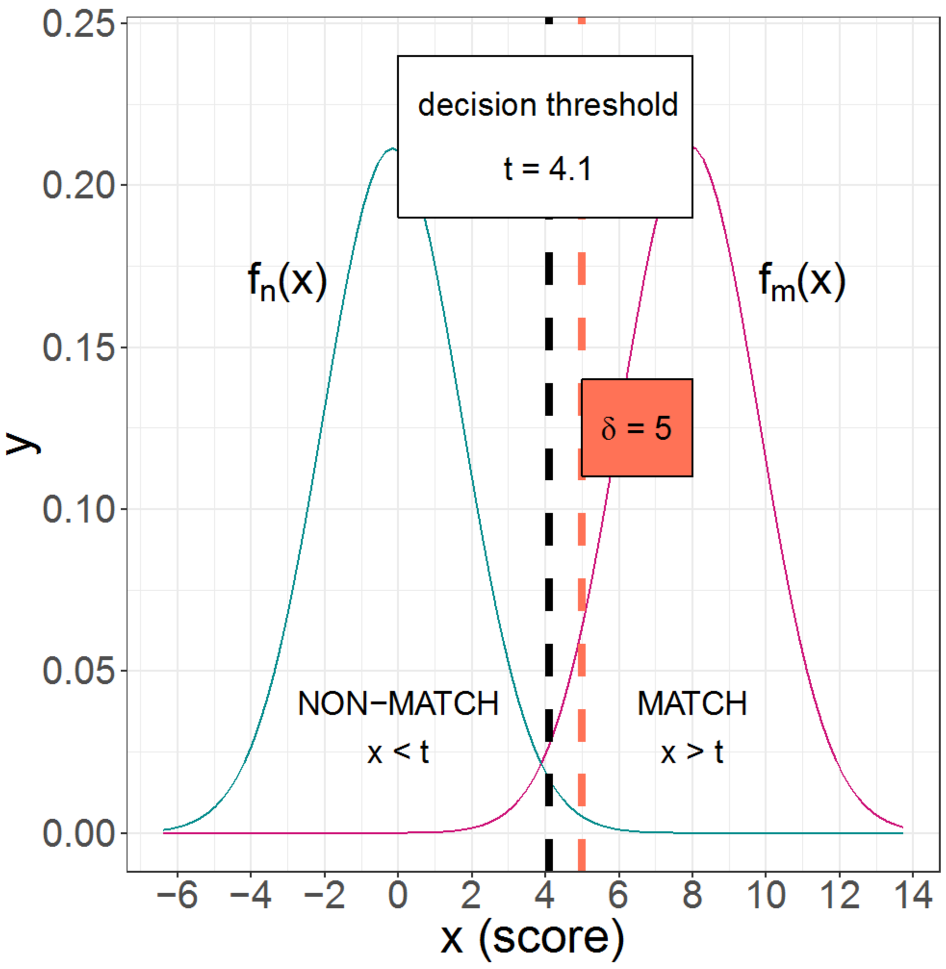
Calculate the score between the questioned image e_u and the suspect's camera e_s

$$\delta = \Delta(e_u, e_s)$$

If $\delta < t$ conclude non-match

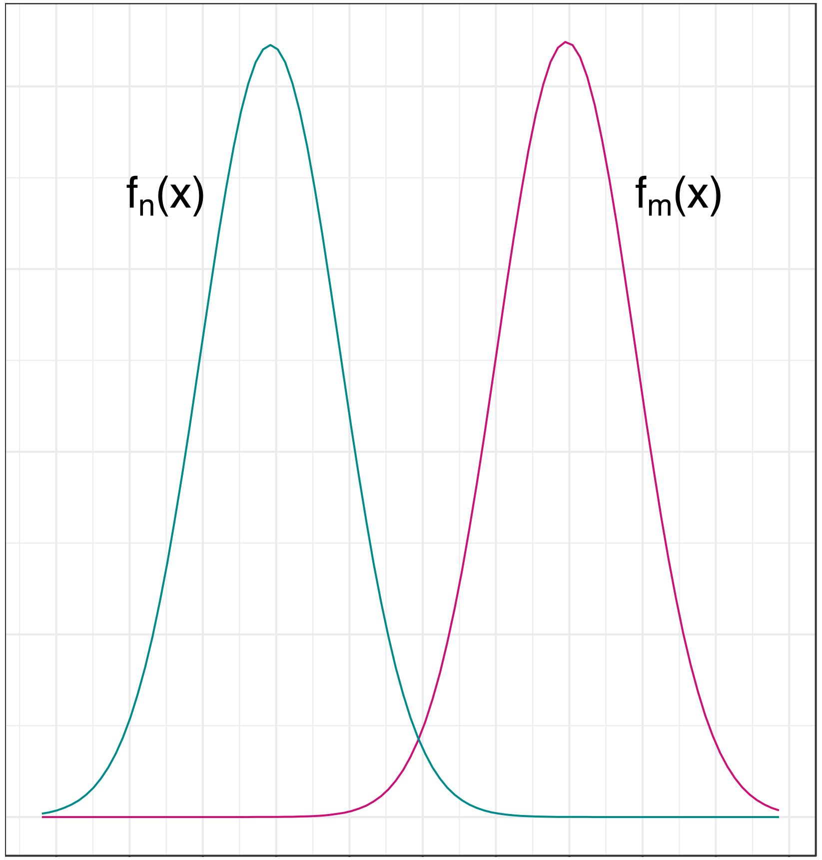
If $d > t$ conclude match

The score $\delta = 5$ is compared to the decision threshold



SLR

Normal pdfs fit to the matching and non-matching scores



SLR

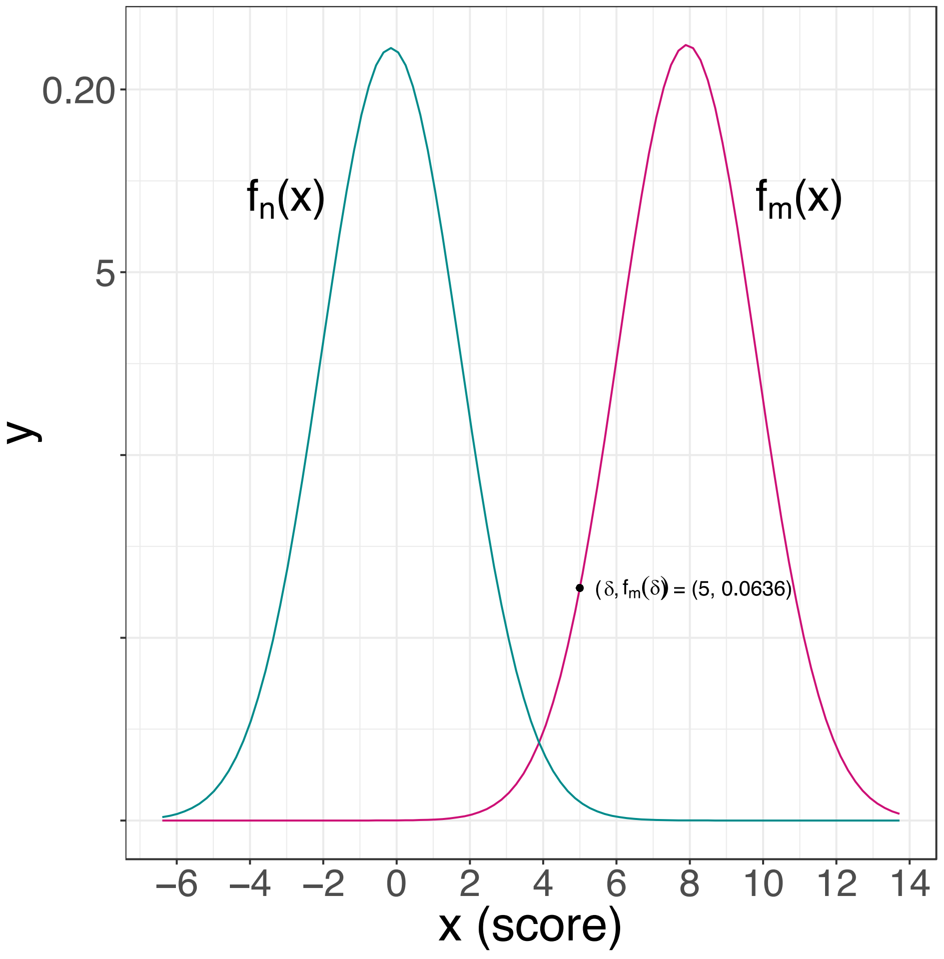
Evaluate pdfs at score δ

Calculate the score between the questioned image e_u and the suspect's camera e_s

$$\delta = \Delta(e_u, e_s)$$

Evaluate $f_m(\delta)$

Normal pdfs fit to the matching and non-matching scores



SLR

Evaluate pdfs at score δ

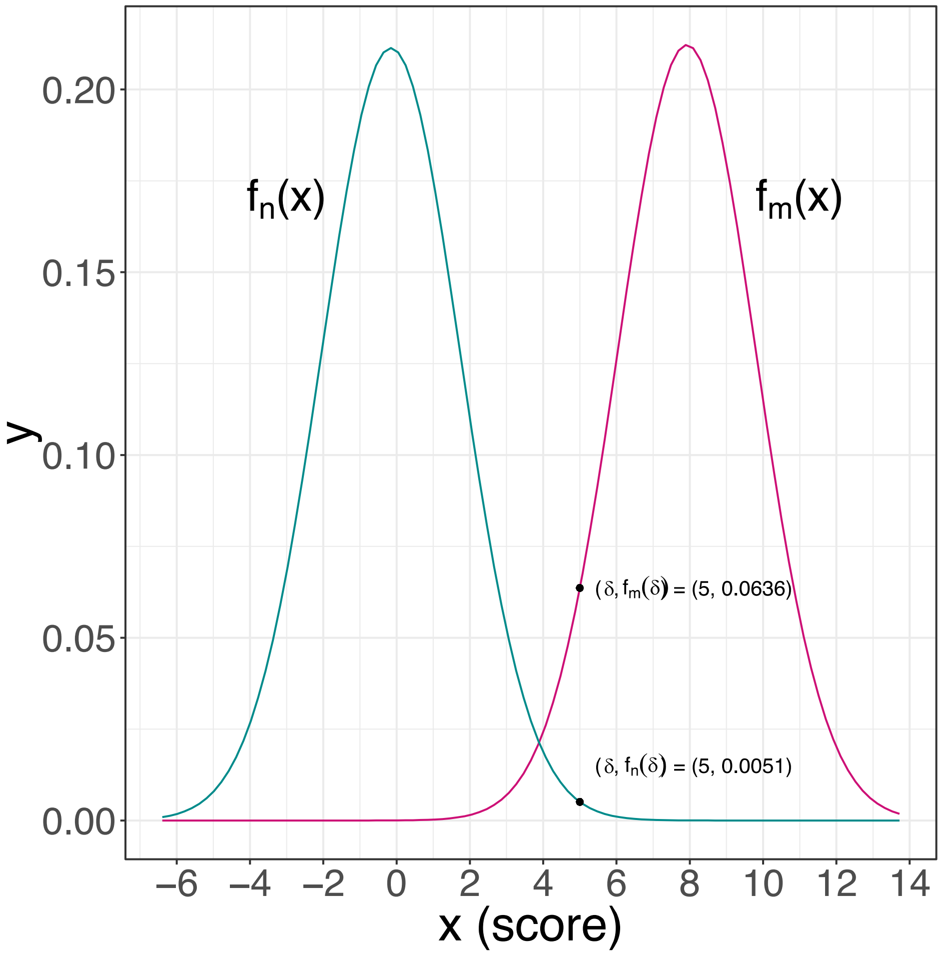
Calculate the score between the questioned image e_u and the suspect's camera e_s

$$\delta = \Delta(e_u, e_s)$$

Evaluate $f_m(\delta)$

Evaluate $f_n(\delta)$

Normal pdfs fit to the matching and non-matching scores



SLR

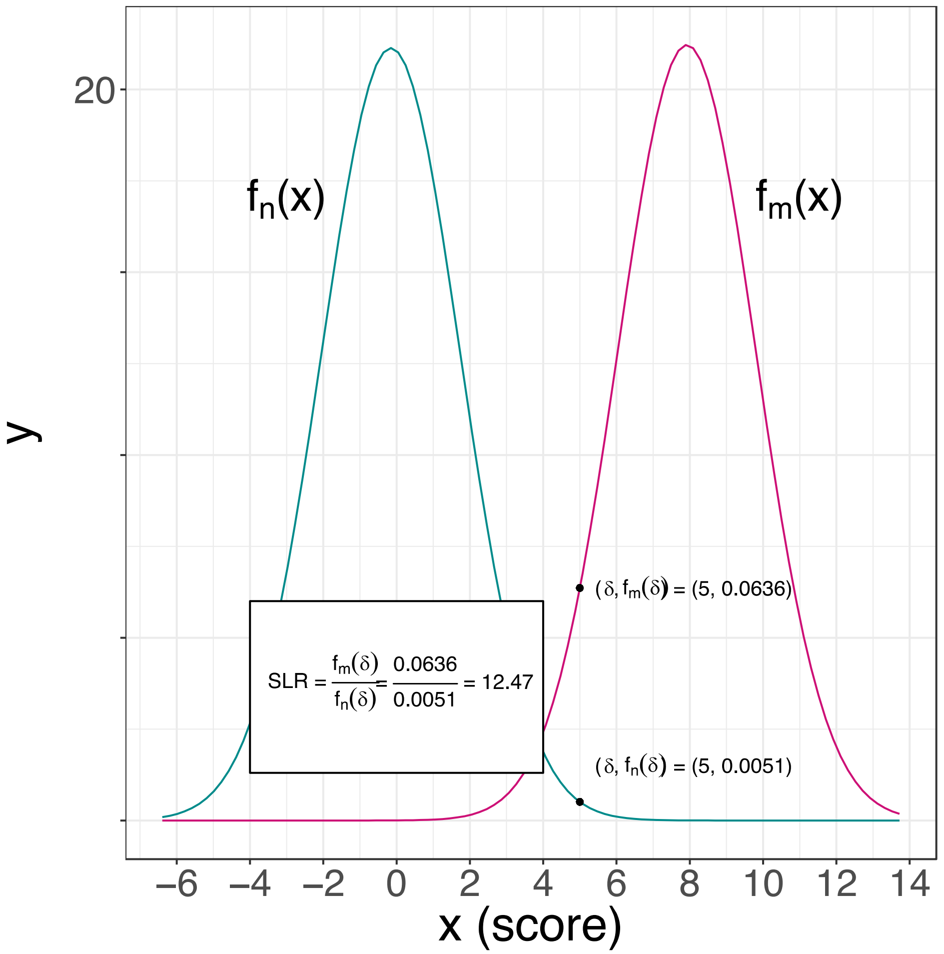
Compute the SLR

$$SLR = \frac{f_m(\delta)}{f_n(\delta)}$$

Example

- SLR = 12.47
- The likelihood that e_u and e_s originated from the same device C_s is 12.47 times larger than the likelihood that they don't both originate from device C_s

Normal pdfs fit to the matching and non-matching scores



Experiments

- 10,000 images from BOSSbase image dataset
- 7 digital still camera devices
- The original images were taken in the native camera formats
- We processed the images:
  - Converted images to TIFF in Photoshop
  - Center-cropped to 512 x 512 and saved as PNG in Matlab
- We used the PRNU extraction code created by DDE Labs
  - http://dde.binghamton.edu/download/camera_fingerprint/
  - (Thanks DDE labs!)

Experiment settings

- We estimated each PRNU camera fingerprint from 50 randomly selected images
- We used the similarity score $\Delta(x, y) = 1 - \frac{(x-\bar{x})(y-\bar{y})}{||x-\bar{x}||||y-\bar{y}||}$
- We calculated non-matches using the trace-anchored method
- We used kernel density estimation to fit probability density functions f_m and f_n to matching scores and non-matching scores

Assumptions

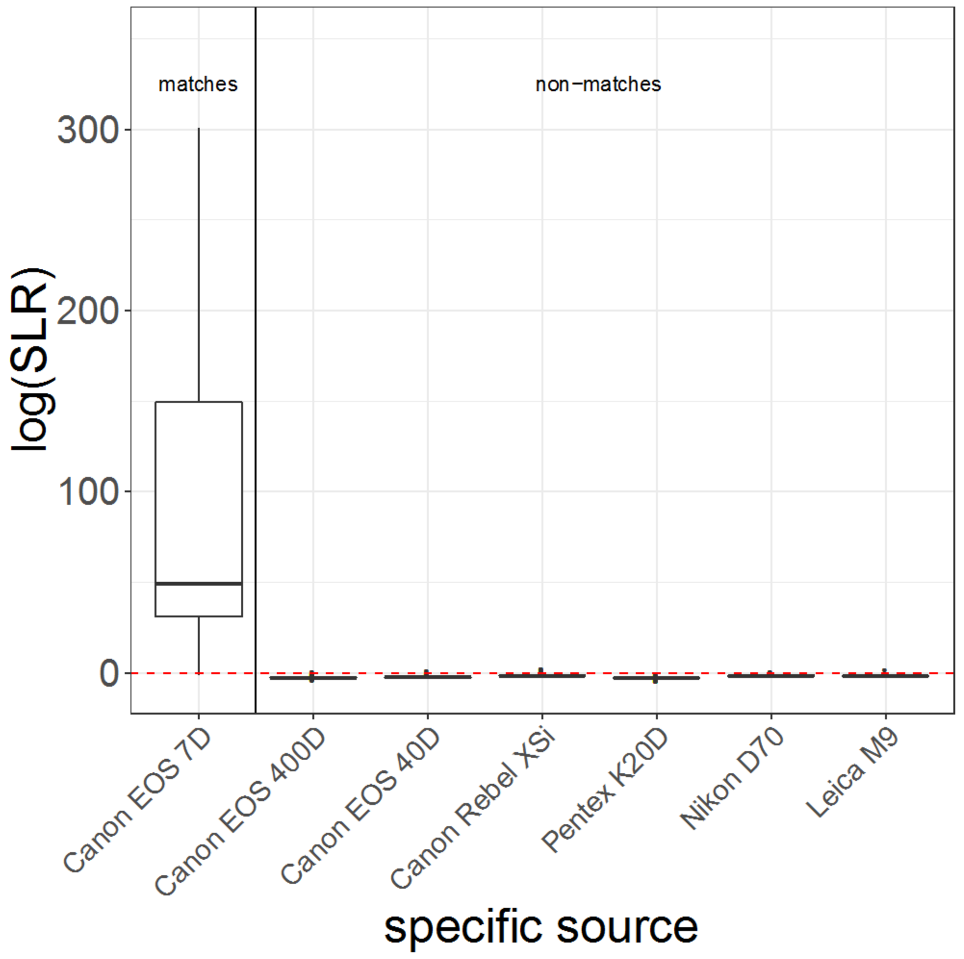
- All images are the same size
- Images have not been resized, compressed, or transformed in other ways

Algorithm

For each questioned image e_u from **Canon EOS 7D**

- For each BOSSbase device C_s
  - Compute camera fingerprint e_s from C_s
  - Calculate $SLR(e_u, e_s)$

Boxplots of SLR values. Questioned images are from **Canon EOS 7D**

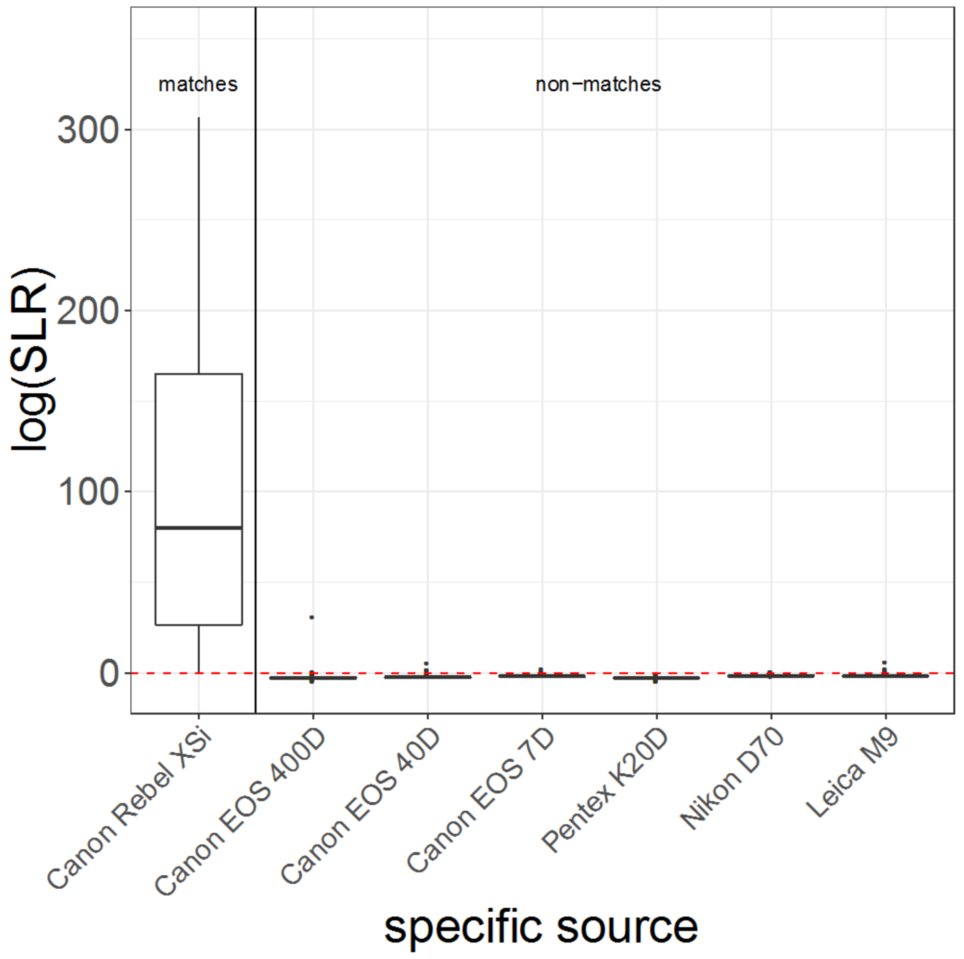


Boxplots of SLR values. Questioned images are from **Canon Rebel XSi**

Experiments

For each questioned image e_u from **Canon Rebel XSi**

- For each BOSSbase device C_s
  - Compute camera fingerprint e_s from C_s
  - Calculate $SLR(e_u, e_s)$

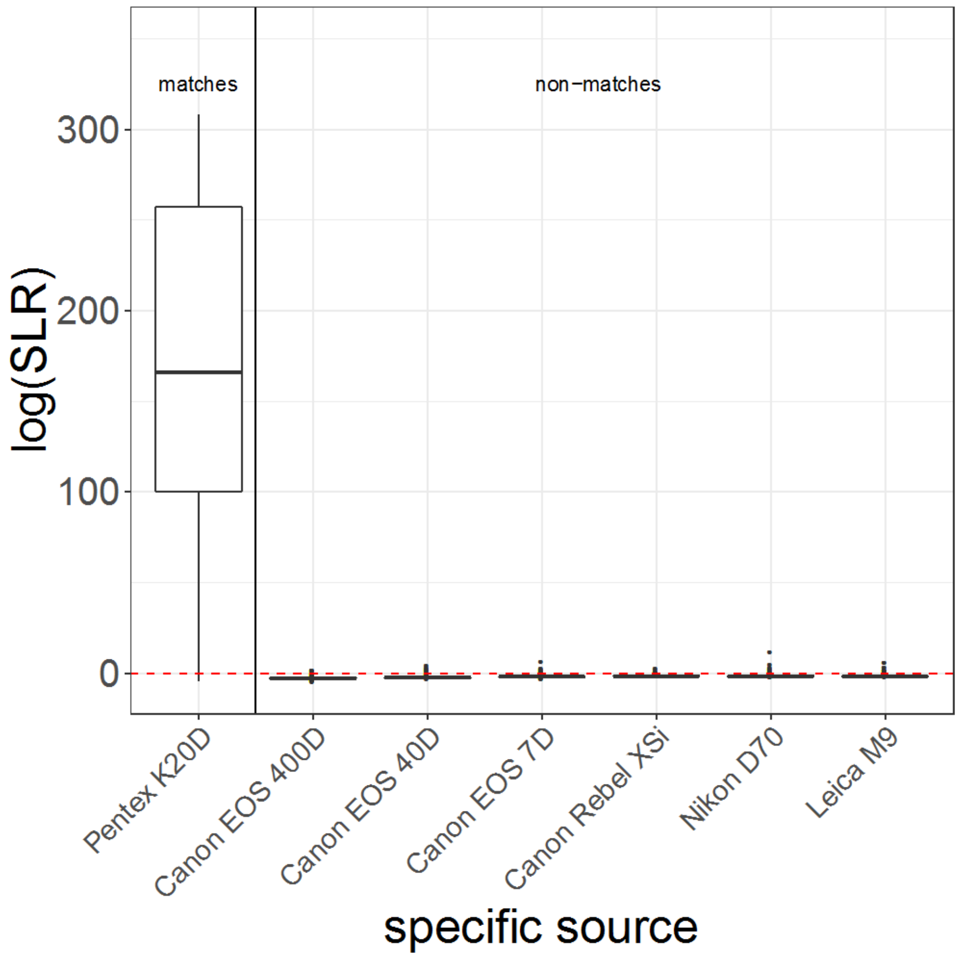


Experiments

For each questioned image e_u from **Pentex K20D**

- For each BOSSbase For each BOSSbase device C_s
  - Compute camera fingerprint e_s from C_s
  - Calculate $SLR(e_u, e_s)$

Boxplots of SLR values. Questioned images are from **Pentex K20D**

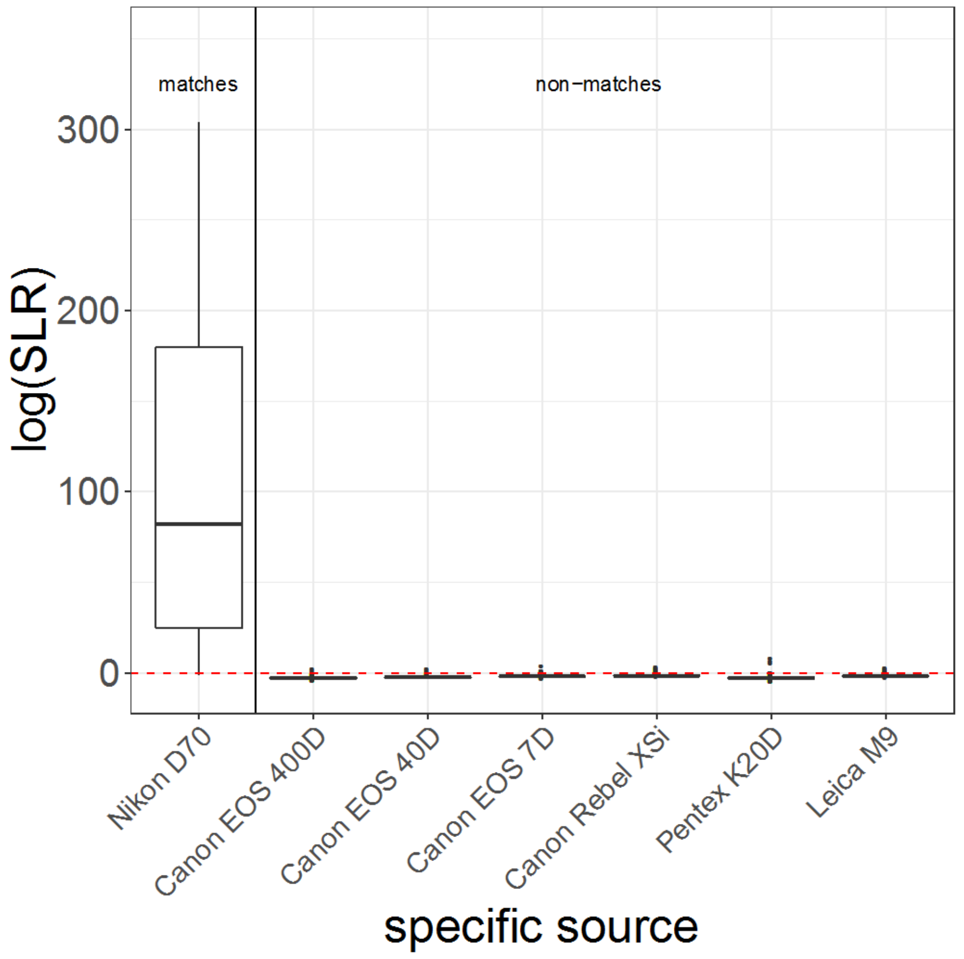


Experiments

For each questioned image e_u from **Nikon D70**

- For each BOSSbase device C_s
  - Compute camera fingerprint e_s from C_s
  - Calculate $SLR(e_u, e_s)$

Boxplots of SLR values. Questioned images are from **Nikon D70**

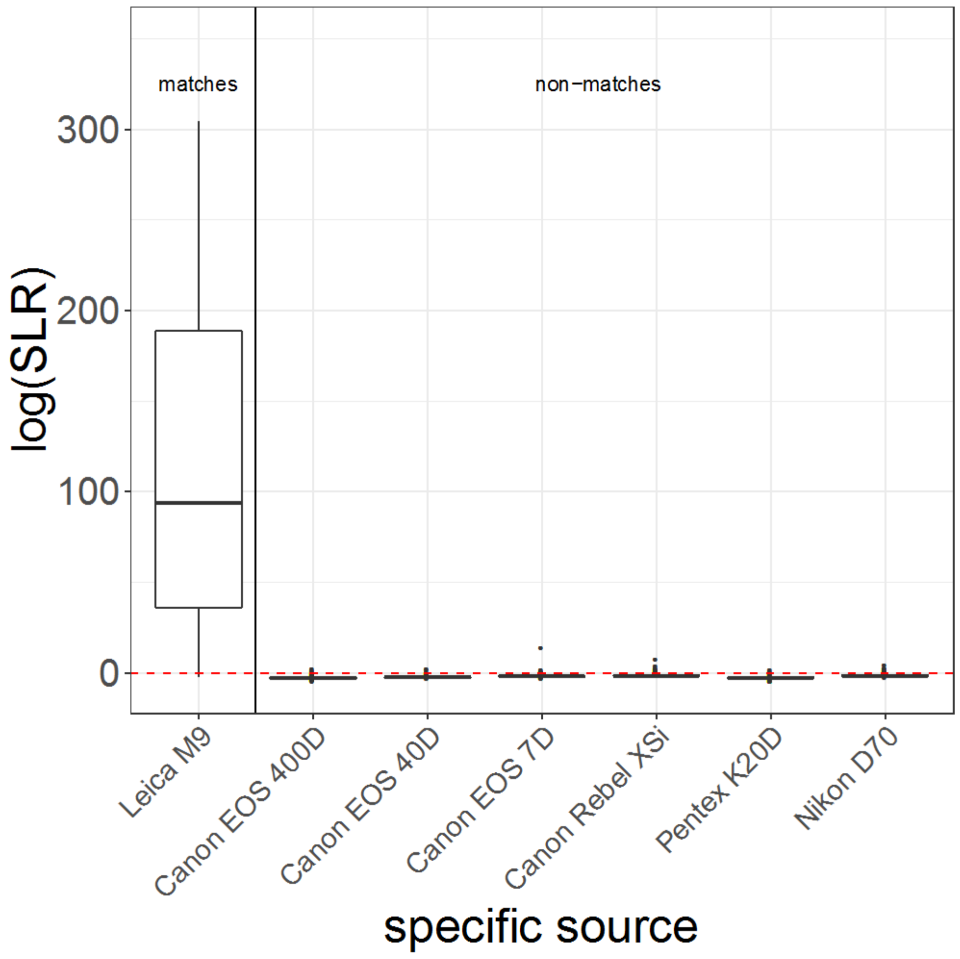


Experiments

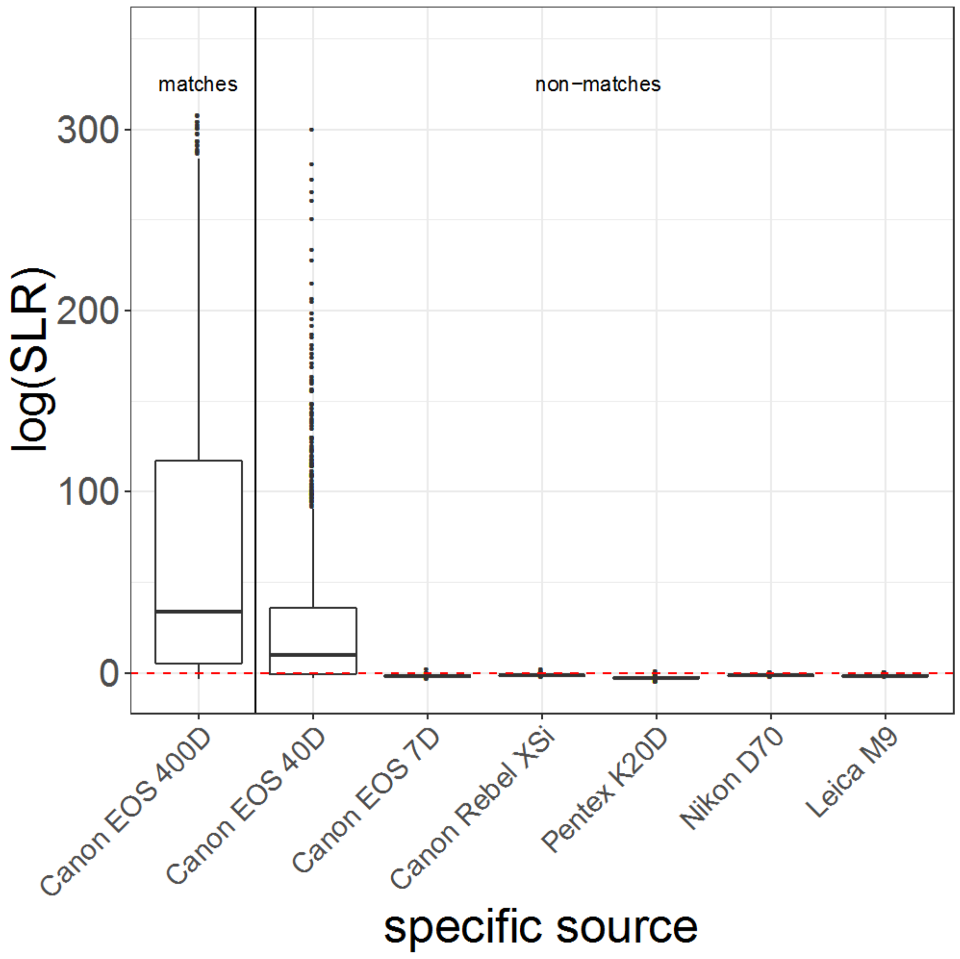
For each questioned image e_u from **Leica M9**

- For each BOSSbase device C_s
  - Compute camera fingerprint e_s from C_s
  - Calculate $SLR(e_u, e_s)$

Boxplots of SLR values. Questioned images are from **Leica M9**



Boxplots of SLR values. Questioned images are from **Canon EOS 400D**



Experiments

For each questioned image e_u from **Canon EOS 400D**

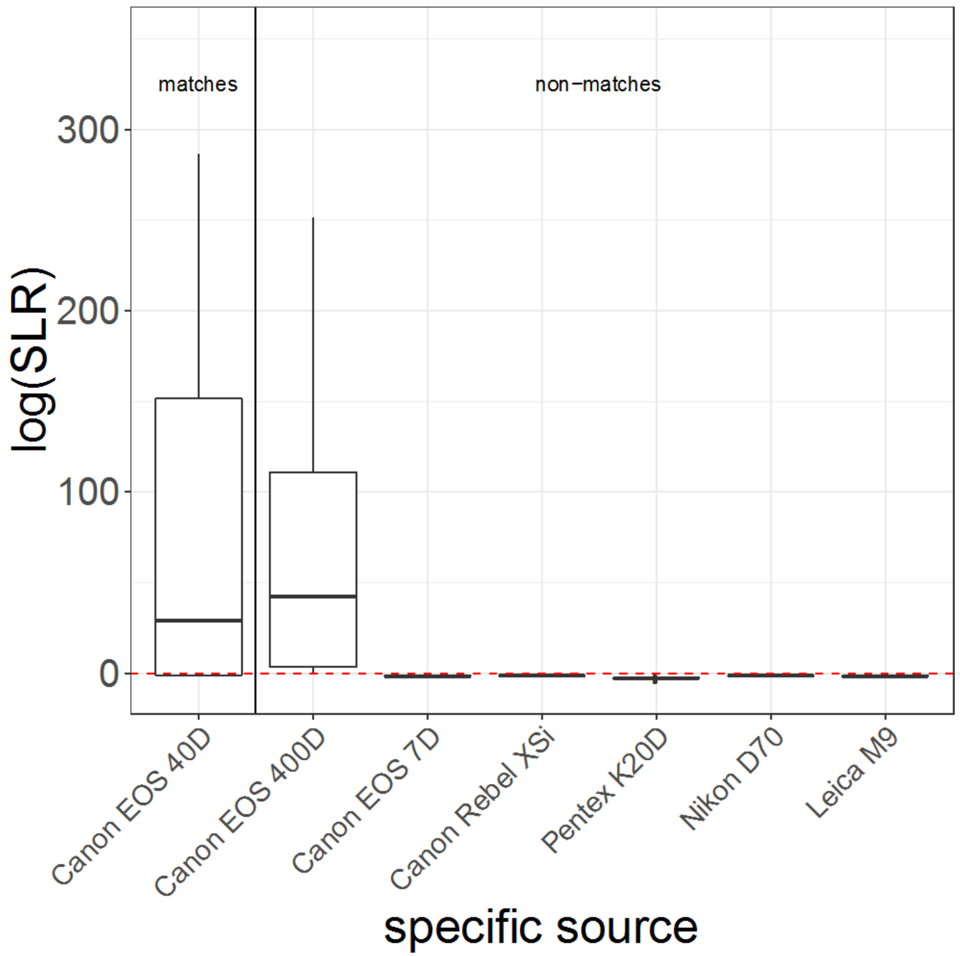
- For each BOSSbase device C_s
  - Compute camera fingerprint e_s from C_s
  - Calculate $SLR(e_u, e_s)$

Experiments

For each questioned image e_u from **Canon EOS 40D**

- For each BOSSbase device C_s
  - Compute camera fingerprint e_s from C_s
  - Calculate $SLR(e_u, e_s)$

Boxplots of SLR values. Questioned images are from **Canon EOS 40D**



Summary and conclusions

- SLR provides a quantification of the weight of evidence
- SLR correctly returns high values for true matches (an image and the device it came from) for all 7 devices
- SLR incorrectly returns high values for images from Canon EOS 400D or Canon EOS 40D when compared to the other device

Future work

- Identify the cause of misleading SLR values for the Canon EOS 400D and Canon EOS 40D
- Compare source-anchored, trace-anchored and general match SLRs for camera device identification
- Extend results to more camera devices using other image datasets
  - ALASKA
  - StegoAppDB
- Extend results to different sized images and image that have been resized or compressed

Acknowledgements

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Maximum SLR

- We calculated the SLR for questioned image e_u and each specific device e_s
  - Each image e_u has 7 SLR values, one for each device
- For each image e_u we find the device e_s that produces the maximum SLR for e_u

Maximum SLR

		Specific Known Device e_s						
		Canon EOS 400D	Canon EOS 40D	Canon EOS 7D	Canon Rebel XSi	Pentex K20D	Nikon D70	Leica M9
Questioned Image e_u	Canon EOS 400D	**92.47%**	7.46%	0%	0%	0%	0.07%	0%
	Canon EOS 40D	31.45%	**67.21%**	0%	1.64%	0%	0%	0%
	Canon EOS 7D	0%	0%	**100%**	0%	0%	0%	0%
	Canon Rebel XSi	0.13%	0%	0%	**99.74%**	0%	0%	0.13%
	Pentex K20D	0%	0%	0.14%	0.14%	**97.05%**	0.07%	0.07%
	Nikon D70	0%	0%	0%	0%	0%	**100%**	0%
	Leica M9	0%	0%	0%	0.07%	0%	0.37%	**99.56%**

- For 92.47% of the images from Canon EOS 400D, the highest SLR value occurred when Canon EOS 400D was set as the specific known device